Recognition Optimization of License Plate Targets based on CRNN

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Abstract

After the license plate area is obtained through the license plate location, a certain license plate recognition algorithm needs to be used to realize the license plate characters recognition. Previous researchers mainly segmented the localized license plate into characters, and then recognized a single character to achieve the purpose of license plate recognition. However, the disadvantage of this method is that the accuracy of character cutting is relatively high. Once the wrong cutting of characters occurs, it will directly affect the effect of license plate recognition. Therefore, we do not cut the license plate. We design an end-to-end license plate recognition algorithm, and introduces the RCNN network into the license plate recognition task. Experiments show that the algorithm designed in this paper effectively improves the accuracy of license plate recognition.

Keywords

License Plate Recognition; CRNN; CNN.

1. Introduction

In recent years, the number of vehicles has greatly increased, which in turn has increased the burden of traffic management. This problem has promoted the development of automated systems that can completely monitor cars and greatly reduce the burden of traffic management. Therefore, this method has attracted great attention from researchers.

The current common license plate recognition algorithms include traditional license plate recognition algorithms and recognition algorithms based on deep learning networks. Traditional license plate recognition algorithms include a license plate recognition algorithm based on template matching and a license plate recognition algorithm based on feature matching, but they usually need to preprocess the license plate image first. The recognition algorithm based on the convolutional neural network puts the localized license plate image directly into the convolutional neural network for training, and uses the neural network to extract character features and classify. At the same time, the recurrent neural network with its excellent ability to combine context is conducive to better recognition of character sequences.Inspired by the above algorithm, we decided to use CNN and RNN for license plate recognition. Experiments have proved that the CRNN-based license plate recognition algorithm improves the accuracy of license plate recognition.

2. Related Work

In this section, we briefly introduce the related work about license plate recognition. In recent years, computer vision technology has continued to develop, and great achievements have been made in the field of license plate recognition.

Many researchers use computer vision technology for the improvement of license plate recognition. Lee Eung Ju [1] et al. improved the contrast between the license plate area and the background area by performing noise reduction and brightness compensation operations on the license plate image, thereby obtaining the license plate recognition result. Kwang-Baek Kim [2] et al. used the morphological information of the horizontal and vertical edges to extract the license plate from the license plate image, and used the SOM algorithm to recognize the license plate characters. Nicolas Thome [3] et al. used a hybrid strategy combining statistics and structural algorithms for character recognition, and introduced a cognitive cycle to realize the recognition of license plates in different countries. Sedighi, Amir [4] et al. used a Gaussian low-pass filter to reduce noise, and used two feedforward neural networks for character recognition, which has good robustness in harsh imaging environments. Gilles Silvano [5] et al. focused on a large number of training samples required for deep learning training, proposed a license plate generation algorithm, and tested it with real parking lot and camera data, and finally achieved 95% detection accuracy.

3. Methodology

3.1 Network structure

The CRNN network regards text as a continuous sequence, so there is no need to perform segmentation operations, and end-to-end text recognition is realized. Based on this idea, we regard the license plate as a complete object, and the license plate picture can be directly used as the input of the network to obtain the recognition result of the license plate characters [6]. The structure of CRNN-based license plate character recognition network is shown in Fig 1, which consists of three parts: convolutional layer, recurrent layer, and transcription layer.

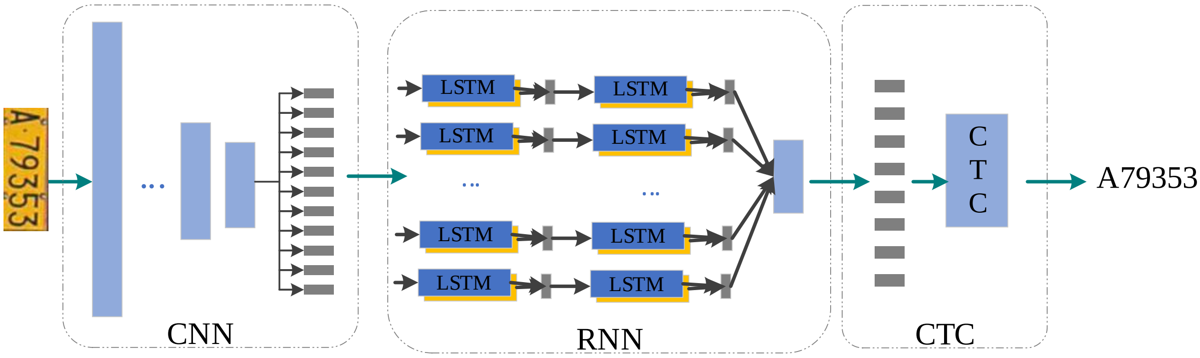

Fig. 1 CRNN network structure

The convolution layer realizes the feature extraction of the license plate image through the continuous convolution of the convolution kernel, and generates a set of feature maps. Then the feature maps are sequenced through Map to Sequence, and the integrated sequence features are sent to the bidirectional long and short-term memory network (BLSTM), and finally the predicted probability value of the license plate character sequence is output. Finally, through the CTC model of indefinite length, the repeated label distribution and redundant information obtained from the cyclic layer are deleted, and the result is converted into the final license plate character recognition result [7]. This algorithm combines the feature extraction capabilities of convolutional neural networks with the timing processing capabilities of cyclic neural networks to realize end-to-end license plate character recognition.

3.2 Convolutional layer feature extraction

The convolution feature extraction in the CRNN network uses the VGG-16 framework. Since most of the license plate images are longer in length and narrower in width, in order to adapt to the size characteristics of the license plate, the size of the convolution kernel of the last two pooling layers is 1×2. In this way, feature maps with different lengths and widths can be generated, effectively taking into account the size characteristics of the text sequence. The BatchNormalization [8] module is introduced to speed up model training and convergence speed, and shorten the training process. The parameter configuration of the convolutional layer is shown in Table1.

In table 1, #number represents the number of convolution kernels used by the layer network, and #units represents the number of hidden layer units in the recurrent layer. The parameter s represents the step size of the movement, k represents the size of the convolution kernel, and p represents the filling size of the boundary area during convolution.

Before sending the license plate image to the network for training, it needs to be normalized in size, and all the license plate images are normalized to 32×100×3. In most cases, the license plate is a rectangle with a relatively large length and width, so consider using different standards for quantification in the pooling layser to prevent losing the license plate width information. In this article, after the license plate image is extracted layer by layer through the convolutional layer, the height is reduced from 32 to 1, and the width is reduced from 100 to 25.

Table 1. CRNN network parameter configuration

Network	Parameter
BLSTM	#units:256
BLSTM	#units:256
Map-to-sequence	-
Convolution	#number:512,s:1,p:1,k:2*2
Max-pooling	s:2,Window:1*2
Batch Normalization	-
Convolution	#number:512,s:1,p:1,k:3*3
Batch Normalization	-
Convolution	#number:512,s:1,p:1,k:3*3
Max-pooling	s:2,Window:1*2
Convolution	#number:256,s:1,p:1,k:3*3
Convolution	#number:256,s:1,p:1,k:3*3
Max-pooling	s:2,Window:2*2
Convolution	#number:128,s:1,p:1,k:3*3
Max-pooling	s:2,Window:2*2
Convolution	#number:64,s:1,p:1,k:5*5
Input	-

4. Experience of Result and Comparison

4.1 Experimental environment

The proposed experiment is implemented under the following framework.

Table 2. Experimental Environment

Name	version
Operating system	Windows 10
CPU	Intel i7-8700, 3.2G Hz
GPU	GeForce RTX 2070 8GB
Additional library	OpenCV
Deep learning framework	Keras Tensorflow

4.2 Experimental results and analysis

In training, the normalized size of the license plate image is 32×100×3. It should be noted that the height of the feature map output by the convolutional layer is 1 at the end. In training, the initial learning rate is set to 0.01, the size of each batch is set to 32, and a total of 50,000 iterations are performed. The SGD momentum parameter of the loss optimizer is set to 0.9. The proposed algorithm uses two-way BLSTM, and each LSTM unit has 256 hidden nodes.

In order to further verify the effectiveness of the algorithm in this section, different license plate character recognition algorithms are used for comparison on the self-built data set. OpenALPR is an open source license plate recognition system for analyzing license plates in images and video streams. SightHound provides license plate recognition services in many countries.

It can be seen from Table 3 that the algorithm in this section has a recognition rate of 96.3% on the self-built license plate data set, which has a good license plate recognition effect and can meet the requirements of license plate character recognition.

Table 3. Algorithm Accuracy Comparison

algorithm	accuracy
SightHound	93.1%
OpenALPR	94.3%
CRNN	96.3%

5. Conclusion

In this paper, we introduce a CRNN-based license plate character recognition method. The experimental results show that the CRNN-based license plate recognition model has a high accuracy rate, which plays an important role in the license plate recognition in complex scenes.

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